POTENTIAL EFFECTS OF CLIMATE CHANGE ON RESIDENTIAL WILDFIRE RISK IN CALIFORNIA

A Paper From:
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DRAFT PAPER

DISCLAIMER

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Preface

The California Energy Commission's Public Interest Energy Research (PIER) Program supports public interest energy research and development that will help improve the quality of life in California by bringing environmentally safe, affordable, and reliable energy services and products to the marketplace.

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In 2003, the California Energy Commission's PIER Program established the **California Climate Change Center** to document climate change research relevant to the states. This center is a virtual organization with core research activities at Scripps Institution of Oceanography and the University of California, Berkeley, complemented by efforts at other research institutions. Priority research areas defined in PIER's five-year Climate Change Research Plan are: monitoring, analysis, and modeling of climate; analysis of options to reduce greenhouse gas emissions; assessment of physical impacts and of adaptation strategies; and analysis of the economic consequences of both climate change impacts and the efforts designed to reduce emissions.

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For more information on the PIER Program, please visit the Energy Commission's website www.energy.ca.gov/pier/ or contract the Energy Commission at (916) 654-5164.

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Abstract

We model the interaction of climate-dependent wildfire risk and one spatially explicit population growth scenario in California to generate measures of changes in wildfire risk to residential property under different scenarios for future climate. While absolute estimates are affected by multiple uncertainties, the following conclusions appear robust to those uncertainties explored: Wildfire risk increases throughout the century in both high emission (A2) and low emission (B1) climate scenarios. There is little noticeable difference between A2 and B1 *Special Report on Emission Scenarios* scenarios for the periods 2005–2035 and 2035–2065, but the higher emission A2 scenario does lead to noticeably higher fire risk in the 2070–2100 period when compared to a B1 climate. Average annual monetary impacts due to home loss may easily prove to be in the billions of dollars by mid-century.

Keywords: Fire, wildfire, risk, climate, scenario, WUI, wildland-urban interface, spatial

1.0 Introduction

Wildfires in California routinely threaten people and property, destroy homes, force evacuations, and result in the death or injury of some citizens and firefighters. As described in the companion report (Westerling et al. 2009) and previous work, climate change can affect the size and frequency of wildfires in California, and do so differentially across the state (Westerling and Bryant 2008, Westerling, Hidalgo et al. 2006, and Lenihan, Drapek et al. 2003). And while fire poses many hazards, its most direct impact on humans is fundamentally connected to how people are distributed over the state. Thus, to better create a reasonable picture of how the California population will be affected by changing wildfire patterns, it is important to consider both climate-induced changes in wildfire and the interactions of these changes with growth.

The primary aim of this report is to describe how climate change and human development patterns over California may interact to lead to differing levels of fire-caused risk to human residences. In this report, we examine how two climate change scenarios (high emission A2 and low emission B1) interact with one plausible growth scenario to yield estimates for residential wildfire risk under a variety of uncertainties. In order to mitigate the impact of uncertainties, our primary results are in the form of statistics on aggregate statewide relative risk (referenced to the year 2000), though we also present relative risk distributions mapped over the state of California, in addition to highly caveated estimates for possible monetary damages related to housing loss.

In the remainder of the introduction, we discuss the impacts associated with wildfire in present-day California, including the many types of impacts that are not addressed in this report. We then provide a brief overview of our general approach to modeling and the outcome measures we use to present the climate impacts.

1.1. Types of Wildfire Impacts

Wildfire impacts humans and the environment in many ways. The most apparent costs arising from wildfires are those of fighting the fires, and the cost of the homes and other structures burned by wildfires that encroach into populated areas. These events can be extreme and receive much attention - in one week in October 2003 over 3000 homes were destroyed, 26 lives were lost and 3000 square kilometers were burned (Keeley, Fotheringham et al. 2004, Westerling et al. 2004). In October 2007, over 350,000 households were evacuated in response to wildfires in southern California (Reza, Leovy et al. 2007). But there are many other less obvious impacts, both to humans and also to ecosystems, some of which are listed in Table 1. (See the California Forestry Board's California Fire Plan for an extremely thorough attempt at comprehensively assessing wildfire impacts of all sorts). In this paper we focus only on quantifying changes in direct damages to homes, and therefore when evaluating our results it is important to remember that these impacts represent just a fraction of the total impacts from wildfire. While monetization of many of the impacts listed in Table 1 is difficult, the California Department of Forestry estimated that, for example, watershed impacts of wildfire, in the form of soil erosion and potential required sediment removal from water bodies, may easily average out to magnitudes on the order $100 per acre burned, possibly even up to thousands of dollars per acres burned in some cases (California Forestry Board 1996). This translates to at least tens of millions of dollars of annual impacts from that source alone. In addition, many of the environmental impacts have human consequences. The health and viewshed impacts of reduced air quality are readily apparent, but there are other more subtle effects, such as watershed impacts reducing desired fish populations and reducing power generation ability from hydroelectric dams.

Table 1. Example types of wildfire impacts

Direct Human Impacts	Indirect Impacts
Structures burned/property value lost	Watersheds - soil loss, deposits
Suppression expenditures	Timber loss
Evacuation costs/lost productivity	Habitat disruption
Lives lost and adverse health effects of smoke	Species loss
Diminished recreational opportunities and viewsheds	Non-native species invasion
Disruption to infrastructure availability	

When considering damages, it is important to acknowledge that wildfire is in principle a natural phenomenon that serves a role in maintaining healthy ecosystems, but human presence and action combine to make fire both a risk to humans, and also potentially a risk to ecosystems. This is due to humans causing unnatural *patterns* of wildfire with intensities or frequencies outside the range of natural variability. For example, fuel suppression may lead to higher intensities, and human presence may lead to higher numbers of ignitions and higher frequencies (Syphard, Radeloff et al. 2007). These changes can impact ecosystems in undesirable ways that may or may not be proportional to the residential impacts we address here.

1.2. Primary Approach: Aggregate Relative Risk

There is a great deal of uncertainty involved in essentially every aspect of wildfire risk scenarios. The model-generated data required to produce our results is at the end of a long chain of cascading uncertainty, thus any individual estimates for a particular year or particular locality cannot be trusted as a "prediction," even contingent on the climate and population scenario.

However, by careful analysis, we can still usefully *compare* different outcomes, while avoiding taking stock in the precise values for any point in time. This involves circumventing the two issues of bias and variance. Bias refers to systematic error in the underlying models that will tend to routinely lead to misestimation in a certain direction. While there is no flawless solution to this problem, it can be addressed to some degree by considering relative risk changes, rather than looking at the absolute estimates. If both estimates are off by a common factor, this will be cancelled out in the relative comparison.

Second, we can help account for random variation at the small scale by only considering significant aggregations over space and also over time. In any given time period and locality, there will be effectively random forces changing the risk by various amounts. But when considered over large enough aggregations, these variations work to cancel each other out, so that the percentage error will be lower when considering impacts over all of California than when considering impacts in a tiny area like the surroundings of a specific town.

While these techniques do not solve all the problems associated with modeling long-term impacts, they help significantly. Thus our primary outputs of interest will be aggregate measures of relative risk. For each combination of climate change scenarios and model uncertainties, we assess the risk summed over all of California relative to the risk in a baseline year, where the risks being compared represent the product of probability of exposure to a fire and the value (number of households) exposed to that fire—though due to fire dynamics, exposed value is less than total value. For the sake of illustration, we do also present some spatially distributed data, along with plausible estimates of monetary impacts under highly caveated assumptions.

2.0 Risk Estimation Methods

The fundamental terms that affect our measures of risk due to wildfire are the expected frequency and size of wildfires, and the population and number of households in areas potentially affected by wildfires. How they are related to generate true risk is not necessarily straightforward, and is a function of many other variables as well. In this section, we first discuss the model-generated data we have available as potential inputs to our own risk modeling, then discuss a conceptual model of wildfire risk. Lastly, we describe how we implement a modeling approach that attempts to capture the important relationships with the data we have available, while minimizing the impact of our missing data and the fundamental difficulty of modeling fire-human interactions.

2.1. Base Input Data at the 1/8 Degree Scale

Because forces governing human-fire interactions act over many scales (Falk, Miller et al. 2007), the appropriateness of any given risk modeling technique is also governed by the spatial scale for which we are considering impacts. In this case, we are constrained by the spatial resolution of available hydroclimatic data. These are available for gridcells of 1/8-degree latitude and longitude (a little less than 14 kilometers between north and south boundaries, less between east and west boundaries). As described in the Westerling et al. companion report (Westerling et al. 2009), climate change models using A2 and B1 emissions scenarios are downscaled to this spatial level and used to force hydrologic simulations. The resulting hydroclimatic data are used to drive statistical models of both the probability of wildfires exceeding arbitrary thresholds (using nonlinear multinomial logistic regression methods), which are then combined with extreme value distributions describing the size of burned areas above those thresholds (using Generalized Pareto Distributions of extremes). Wildfire occurrence and extent is originally estimated monthly for 1950 to 2100, though we rely on annualized time-averaged values for thirty-year windows in generating our risk estimates. The ultimate output of the fire modeling we utilizing is the expected total burned area in wildfires exceeding the 200 ha minimum threshold.

To consider the evolving geographic distribution of population and number of households, we rely on a base case distribution provided by the U.S. Environmental Protection Agency. The Integrated Climate and Land Use Scenarios (ICLUS) were developed to create thematically consistent land use scenarios at high resolution across the United States (US EPA 2008). They link country level population growth assumptions with the SERGOM spatial distribution model to generate housing density projections at the 100 meter (m) level (Theobald 2005). At the time of analysis, spatial housing density data was available only for a midrange case, but not for the A2 and B1 socioeconomic growth conditions. These projections were provided on the 100 m level (hereafter "pixel", in contrast with 1/8 degree "gridcell"). The precise spatial distribution of pixels within 1/8 degree gridcells plays no role in our analysis, though as discussed later we do retain information about the distribution of pixel values within a gridcell, rather than simply aggregating their associated values to the gridcell level. Other methods for assessing fire risk do utilize fine spatial detail to construct buffer zones defining fire risk, under the (justified) assumption that houses may catch fire due to falling embers that land significant distances from the true fire perimeter (FRAP 2003). Due to lack of reliable spatial data decades in the future, our approach is essentially independent of this method, relying instead on density distributions within the gridcell, which may imply an underestimation of risk.

2.2. Conceptual Model of Fire, Exposure and Risk

Climate change has the potential to affect wildfire patterns through multiple channels. One is its effect on vegetation patterns—as climate changes, vegetation patterns may change as well, with plants suited to a specific climate and locale migrating or dying off, and being replaced by plants more suited to the new climate. The combination of vegetation type and moisture patterns (also affected by climate) can change fuel build-up and moisture levels, which in turn lead to different distributions of fire probabilities and fire size.

The distribution of people over the landscape also changes with time. The interaction between humans, landscape and wildfire risk runs through multiple channels as well, some of which work to counteract each other. In one sense, development in a given region decreases the vegetation footprint available for the ignition of wildfires, but human presence may more than compensate by an increase in human-caused ignitions, where there were only natural ignitions before. However, the increased presence of humans may also have the effect of decreasing fire size in the region, through early identification of fires and increased suppression efforts. In general, the statistical relationship between population density and the human-related "risk of fire" is some form of inverted U (or even one having multiple maxima), being zero at zero human presence, and zero at some saturated density, where everything is urban and wildfires cannot exist. However, the range of shapes possible in between these extremes is not known and likely highly contingent on many other variables associated with the locality.

Our model of fire risk accounts for human impacts on wildfire probabilities, and also allows for humans to act in ways that mitigate their exposure to fire proportionally with the value at risk, thereby capturing some of the interactions described above. These relationships are shown conceptually in Figure 1. The first several steps were carried out by other researchers as part of the California Climate Impacts Assessment. The *Special Report on Emissions Scenarios* (SRES) scenarios affect population growth and also emissions. Population growth combined with assumptions about its spatial allocation yields a spatially explicit population trajectory through time. As modeled by Westerling et al. (2009) this population distribution, together with climate change, affects the probability and size of wildfires, both directly and through their joint impact on vegetation change. The focus of the present paper is on the last two steps: Integrating spatial population with exposure assumptions to estimate value exposed to loss from wildfire, and then integrating that exposed value with expected values for area burned by wildfire to generate estimates of risk.

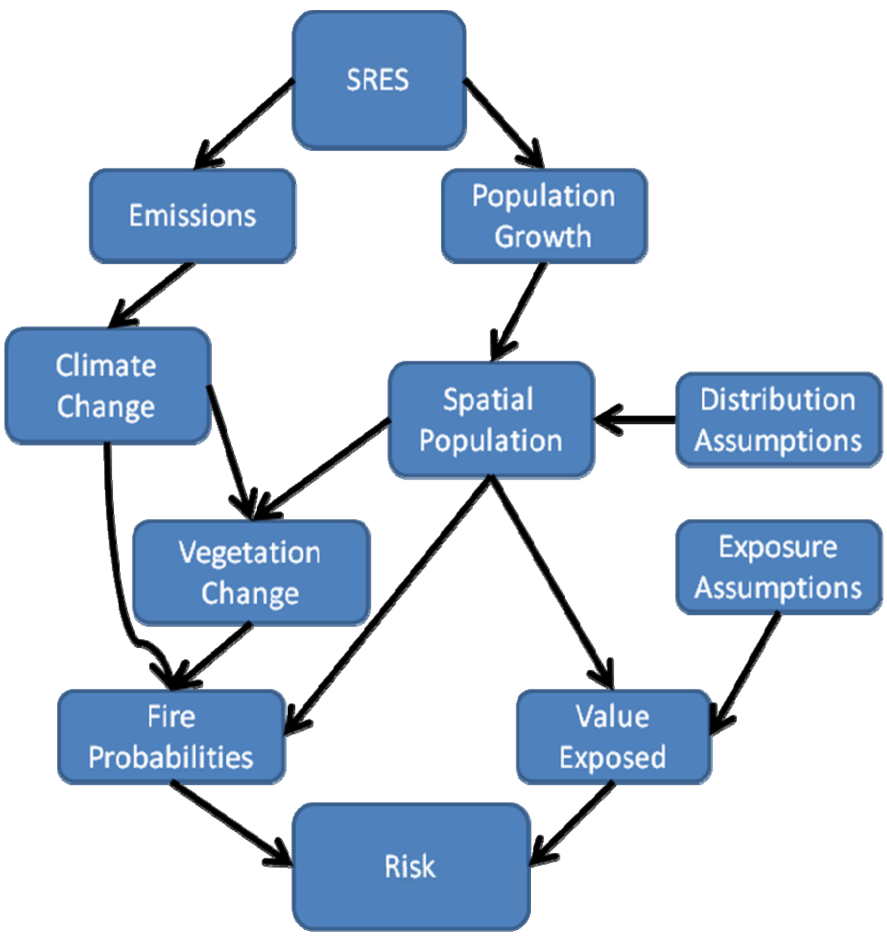

Figure 1. Conceptual model of climate-impacted fire risk

As can be seen from Figure 1, the first way in which human presence is allowed to impact fire probabilities is by incorporating a population term directly into the statistical model of fire probabilities affected by human population growth. This term is allowed to be nonlinear, and has the potential to account for both the increase and decrease in fire risk as population goes from very low to very high density (Syphard, Radeloff et al. 2007).

Human presence also affects fire probabilities through its impact on the available vegetated area over which fire is allowed to start and burn. The fraction of each gridcell covered by vegetation also enters the fire probability model directly, and we adjust this fraction depending on the amount and density of human presence in the gridcell. The precise method by which this allotment is made is discussed in Appendix 1 of the companion Westerling report (Westerling et al. 2009), but essentially we use the spatial urbanization projections to identify how much of each gridcell lies above a certain threshold household density. We then allot that fraction of area proportionally to the different classes of non-developed, non-water areas remaining in the gridcell. The thresholds used to define urban are treated as uncertainties in the model, and affect the variation of our final estimates as described in Section 3.1. Future work will also explore different vegetation allocation methods as well.

In addition to allowing for human presence to affect the baseline wildfire probabilities, we also allow that the amount of value exposed to risk may scale negatively as a function of household density. Here, the concept is that because there exists some density at which an area is urban and no longer subject to the threat of wildfires, there must be some (statistical, rather than deterministic) function which relates the value (e.g., number of homes or households) *existing* in a given area to the value *exposed* to the risk—since it is not necessarily the case that all households in a given area are genuinely at risk for burning due to a wildfire.

These ideas combine into an underlying conceptual model of fire risk for a given gridcell:

$$RISK_{gc} = p(C_{gc}, P_{gc}, V(H_{pix \subset gc})) \times E(A)_{gc} \times \sum_{pix \subset gc} X(H_{pix} s(H_{pix}))$$

Where p is the probability of a large fire above an arbitrarily specified size, C is climate, P is population, and V describes the vegetation fraction at the gridcell level as a function of the household distribution at the pixel level. $E(A)$ denotes the expected burned area conditional on a large fire occurring, expressed as a fraction of the total non-water area of the gridcell. X is the household value exposed at the pixel level, which relates value enclosed to a function $s(H)$, which scales total value in a pixel to the fraction of that value genuinely exposed to risk. The multiplication by area fraction to generate an estimate of risk involves the assumption that exposed value is likely to be lost to wildfire in direct proportion to the size of the wildfire relative to the size of the gridcell. This assumption does not necessarily hold in many cases, but is made irrelevant in discussions of relative risk. It does play a role in our absolute monetary estimates described later.

Components of the fire-estimation methodology are rigorously detailed in Preisler and Westerling (2007) and Holmes, Hugget and Westerling (2008). Here we focus on the estimation of the value-exposed component. The formalized value-exposed model presented here is not based on preexisting work, but is designed specifically for this study in order to quantify the qualitative relationships documented in the literature discussed above. We consider the value exposed to wildfire risk within a gridcell to be a function of the value existing within the gridcell, and also a function of how exposure to fire decreases with increasing household density. In doing this, we do not take into account the explicit spatial location of household distributions at the 100 m level, but we do utilize information about the distribution *of values* associated with the 100 m pixels in each gridcell. That is, we perform our exposure scaling at the 100 m level, and then aggregate the exposure-adjusted values to the 1/8 degree level, rather than first aggregating value enclosed to the 1/8 degree level and then applying the scaling function. The rationale behind this ordering is that protective action against wildfire is more accurately described as taking place at the 100 m level, rather than the ~10 kilometer level. It is likely that the true scale of relevance lies somewhere in between, and future work may explore different spatial scales of aggregation, but such exploration was not undertaken for this project.

The form of the exposure scaling function itself is unknown to us, however we assume it to fall within an envelope of possibilities, and explore the impact of these assumptions. The effect of its precise form should be somewhat diminished in our consideration of relative risk, though it does play a larger role in our analysis on absolute values. To capture a suitable variation in functional form we choose a function satisfying $x^k + y^k = 1$, and allow k to vary. Here x is the ratio of the household density in a 100 m pixel to the "threshold density" above which an area is considered too urban to be subject to wildfires, and y is the fraction by which the existing value is scaled. As can be seen in Figure 2, high values of k imply that not much scaling happens until close to the threshold, while low values of k (below one) imply more drastic scaling even with low densities. Additionally, to the extent that the fire probability model sufficiently accounts for human presence, it may or may not be necessary to normalize these scaling adjustments so that total probability is preserved in the gridcell. In order to address this possibility, we introduce as another uncertainty a normalization factor in which the scaled values are multiplied by the reciprocal of the area under the scaling curve. Additional discussion of this rescaling function is provided in the appendix.

The full functional form for our value exposed to fire in a gridcell is then:

$$\sum_{pix \subset gc} \left(H_{pix} A \left[s(d,k) \right)^{-I} \right] \max\left(s(d,k) \right),0 \right)$$

Where A is the area under the scaling function $s(d,k)$ equal to:

$$s(d,k) = \left[1 - \left(\frac{H_{pix}}{d} \right)^k \right]^{1/k}.$$

The value d represents the threshold density, and I is an indicator function for whether normalization should take place. As a reminder, only H_{pix} is provided as a formal scenario level – s, k, and d are all considered uncertain parameters describing features of human-fire interaction.

It is this expression which is multiplied by the expected burned fraction for a given gridcell and month in order to arrive at a gridcell-level risk estimate.

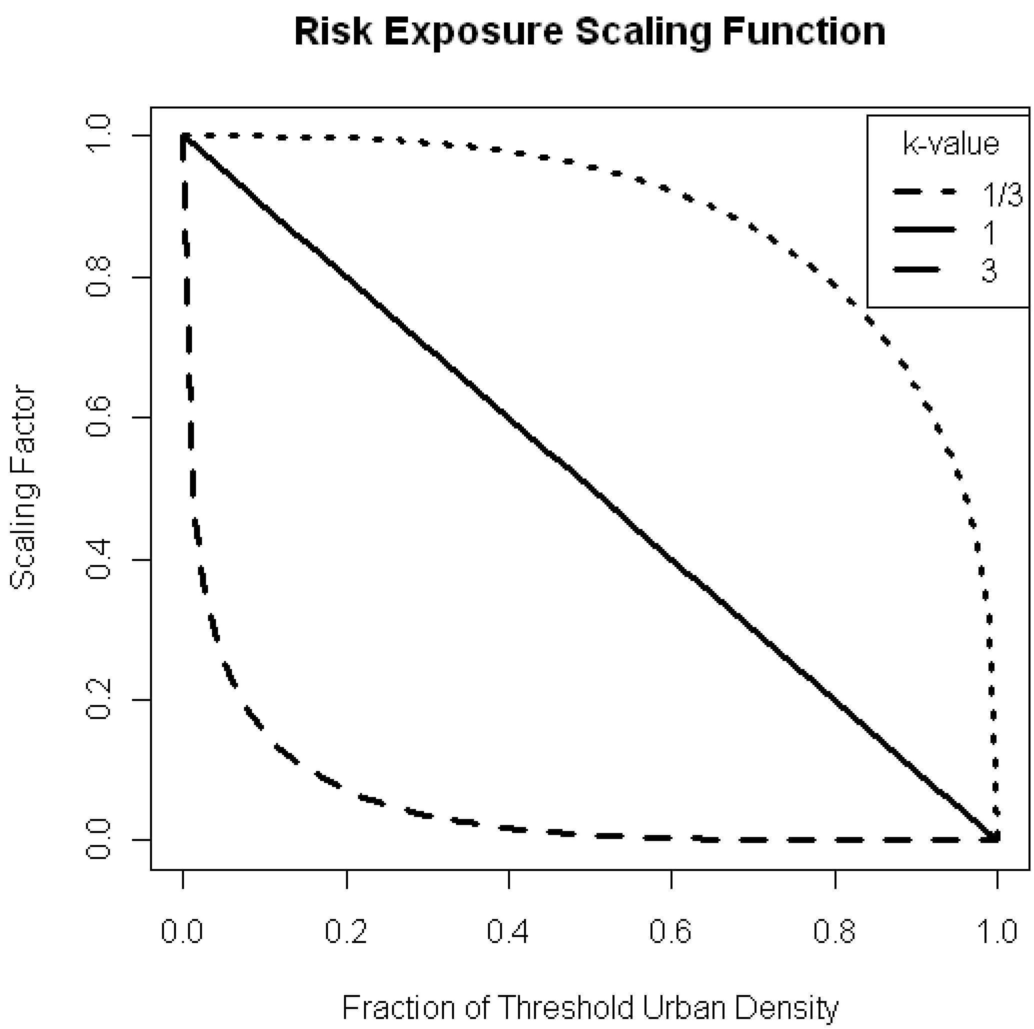

Figure 2. Exposure scaling function for different parameter values

2.3. Aggregate Relative Risk to Address Model Bias and Variance

Both the model for wildfire burned area and the growth model for allocation of residences are likely subject to bias and variance, the statistical terms referring to the size of systematic and random error, respectively. While these problems of bias and variance suggest that we should not place a great deal of confidence in the particular estimated values, we can arrive at still-useful estimates of another form, ones in which we can place more confidence. First, by aggregating the gridcell-level risk to larger geographical regions, we cancel out much of the random variation. Second, if we assume that the bias in the model is approximately proportional to the true model, then this bias will largely cancel when comparing aggregate risk estimates relative to a baseline risk. In order to capitalize on this increase in accuracy, we take as our primary outputs of interest the aggregate relative risk ratios over all of California. Specifically:

$$RR_{CA} = \frac{\sum_{gc \subset CA} p_{gc}(S,T) \times E(A)_{gc} \times X_{gc}(S,T)}{\sum_{gc \subset CA} p_{gc}(S_0,T_0) \times E(A_0)_{gc} \times X_{gc}(S_0,T_0)}$$

That is, we compare the risk in a given scenario S and time period T to the risk in a baseline (historical) scenario, with both calculated under a common set of assumptions.

2.4. Supplementary Illustrative Impacts

We consider two additional forms of impacts that provide more detail of the impacts, with the tradeoff that they are more strongly affected by uncertainties. The first is an illustrative display of statewide risk distributions at the 1/8 degree level. This output format requires no additional calculations—we merely retain the distributions over the state calculated for each gridcell, although the variance-stabilizing effect of aggregating to the state level is then lost.

The second presentation involves estimating monetary impacts associated with statewide fire risks. This requires supplementing our risk model above with additional assumptions in order to arrive at measures of expected value lost. Such a technique was described in Westerling and Bryant (2008), and requires assumptions about housing value and the expected fraction of housing value lost given a housing unit is lost to a wildfire.

For the estimation of housing value, we use year 2000 housing values scaled by the average 10-year increase in statewide inflation-adjusted average housing cost from 1940 to 2000. This is approximately 38 percent (US Census, 2009).

The expected fraction of housing value lost given a house is burned is referred to as the "improved fraction"—this is not equal to 1 because a property retains at least some land value even if the home is lost. Our estimates will be directly proportional to this ratio, so exploration of sensitivity to this value is trivial. Therefore, for this study we simply use .5, the median value utilized by Westerling and Bryant (2008).

Formally, the expected damages function is:

$$E(damage)_{gc} = V \times I \times RISK_{gc}$$

Where V is the housing value, and I is the improved ratio (.5). It is recognized that all of the above factors will in reality be highly property dependent. However, modeling this greater detail decades into the future would be shrouded in such uncertainty that we chose merely to consider illustrative values in this analysis.

2.5. Nominal Calibration Exercises

When model parameters are unknown, it is common to estimate them by finding parameter combinations that generate model behavior consistent with observed data or historical experience. Because there are often multiple combinations of parameters that lead to matching of historical output, successful calibration does not necessarily guarantee the model will predict well when tested outside the period of calibration. However, in our case we can use very basic calibration techniques not to completely restrict our parameters sample, but to provide a reference within which our broader range of uncertainties is explored.

The data we calibrate to is the California Department of Forestry's data on annual structures lost, from 1989 to 2006 (CDF, 2009). Our calibration technique is to fit a linear time trend and estimate 95% confidence intervals around a prediction for the year 2000, and identify which parameter combinations we sampled lead to housing losses within those bounds. Applying this technique, we find a 95% confidence interval on Year 2000 structures lost of 150 to 1501. Under the assumption that all structures lost are homes (discussed below), we find the following risk parameter combinations are consistent with this range:

Threshold urban density (d) =147 and k = 1 and no normalization

Threshold urban density (d) =147 and k = .333 and no normalization

Threshold urban density (d) = 1000 and k = .333 and no normalization

We found that no parameter combination that included normalization and no parameter combination that included a exposure scaling coefficient ('kval') of 3 led to values within even the 99 percent confidence intervals around the year 2000, so we excluded those from our analysis. Our results are then presented in following forms: Our maximal bounds arise from considering as our input space the outer product of parameter values that were plausible individually, while our calibrated cases include only those parameter combinations that actually led to consistent year 2000 values, which we provide for reference. It turns out that our calibration parameter combinations include the lowest bound, so in this case there is no difference between lower calibrated bound and minimum outputs of our uncertainty combinations. The upper bound case not considered as part of the calibrated set is k=1 simultaneously paired with a density threshold of 1000. The relative sensitivity of all the fire-probability uncertainties was much smaller, so all combination of those are included.

Clearly this a very simple first-order calibration exercise with several limitations. First, we make two assumptions regarding the data: One is that all structures lost are housing units, (which biases our results upwards), and one is that all housing units lost fall within CDF jurisdiction (which biases our results downward). These opposite biases should partially cancel each other, but we do not know with which side of zero the net effect lies. Another key issue is that we applied the calibration after our combinations of uncertain parameters were chosen, so that our sampling was not a search process to probe the boundaries of plausible parameters. In reality, many parameter combinations would likely lead to year 2000 values consistent with the damage estimates of our model, but different parameter combinations may cause the model to behave differently farther out in the future, even though they match in historical periods. Future work will explore these implications in more detail.

3.0 Results

3.1. Overall Impacts

Our overall results are captured in the box and whisker plot of Figure 3. The ranges displayed in this plot are contingent on year and emissions scenario, but otherwise all other variables are treated as uncertain, and their variation contributes to the range of estimates for each climate scenario. The variation is due to our pre-specified non-random experimental design over the uncertainties, rather than arising from some probability distribution. Therefore, statistical inferences related to the differences between the resulting distributions should be avoided.

We see that aggregate statewide risk increases with each time period under both emissions scenarios. Additionally, we can see that the effect of different emissions scenarios is nearly indistinguishable through mid century, but that by the 30-year period[1] centered around 2085, the SRES A2 emissions scenario displays noticeably higher risk of property losses due to wildfire as compared to the B1 scenario.

[1] Most scenario analysis for this series of reports reference the 30 year periods 2005–2034, 2035–2064, and 2070–2099. Our spatial housing distributions were available in 10-year increments only, and as these form the core of the estimates for value at risk, they are averaged over the 31 year periods extending one year beyond each of the “standard” periods. The probabilities and expected burn areas are from time averages over the original 30 year periods.

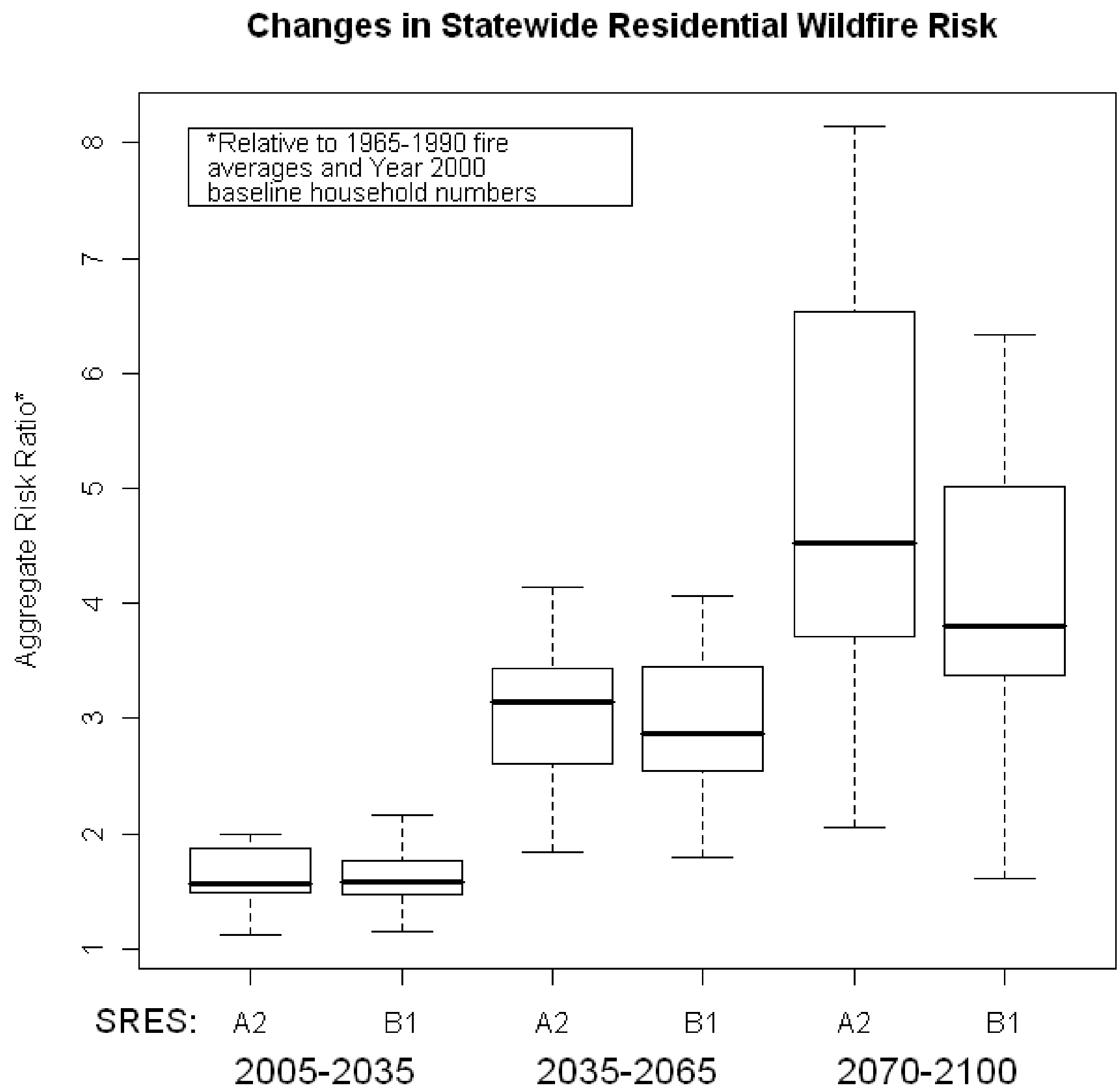

Figure 3. Changes in wildfire risk to households, by time period and emissions scenario

The minimum and maximum values associated with Figure 3 are summarized in Table 2, along with the lower and upper estimates found when applying only the Y2K-consistent parameters. While we discourage taking great stock in the precise values presented, the current model and assumptions used suggest California could experience anywhere between a 61 to 715 percent increase in aggregate fire risk by the end of the century, with a tripling or even quadrupling of fire risk appearing quite plausible by mid-century, under either climate scenario. It can be seen that the ranges on the box-and-whisker plot do extend quite far, especially in 2085. However, the fact that none of the 80 plausible combinations of uncertain parameters yielded a relative risk ratio lower than 1.611 by 2085 suggests we can be reasonably confident the risk will increase substantially, under this particular growth scenario and assuming no drastic improvements in fire protection ability. The growth scenario we utilize does assume a near doubling of population from 2000 to 2100, thus much of the risk increase can be explained by the new population—but the remainder is due to a combination of climate-induced change, and potential changes in growth patterns that create larger exposed value per capita.

Table 2. Relative risk ratios by period. The 'Min' and 'Max' columns represent the bounds of cases we explored. The 'Min' and 'Upper' columns represent the bounds from parameter combinations consistent with Year 2000 damage estimates.

Summary Statistics for Aggregate Relative Risk

	2005-2035			2035-2065			2070-2100		
	Min	Upper	Max	Min	Upper	Max	Min	Upper	Max
SRES A2	1.12	1.93	2.00	1.83	4.14	4.14	2.06	6.82	8.15
SRES B1	1.14	1.99	2.17	1.79	4.07	4.07	1.61	5.42	6.33

3.2. Illustrative Spatial Impacts

Figure 4 displays the spatial distribution of residential wildfire risk throughout the state for the period centered around 2085, using two different climate models and two different climate scenarios. The color scale codes the expected damages in terms of expected annual structures lost, by gridcell. The patterns are similar across the state regardless of model and climate scenario, though it can be seen that for a given model, the A2 scenario shows greater orange and red areas of high risk as compared to the B1 scenario.

These maps demonstrate graphically the important relationship between population and risk, with high risk areas clustering around population centers and the development in the Sierra Nevada foothills. This is a reflection of multiple factors, including population's influence on wildfire itself and the fact that population correlates with structures (homes) exposed to wildfire, as well as the effects of climate on wildfire. While they are assumed to do so here, neither the relationship between population and fire nor the relationship between population and exposed structures must stay fixed through time, which implies a potentially large role for policies to mitigate residential wildfire risk, both through reducing ignitions, and also through better protection of homes. In addition, because we employed a single base-case growth scenario that lies between the population and development that would be consistent with the SRES A2 and B1 storylines, the differences between modeled risks for the A2 and B1 scenarios (Figure 4) are less than they should otherwise be if we assume consistency between California's development narrative and that of the world. That is, the effects on our relative risk measure of the greater burned areas in the A2 scenarios would be compounded by greater population growth and more sprawl, and vice versa for the B1 scenarios. The analysis reported here will be extended in the near future to incorporate new ICLUS growth scenarios compatible with the A2 and B1 storylines.

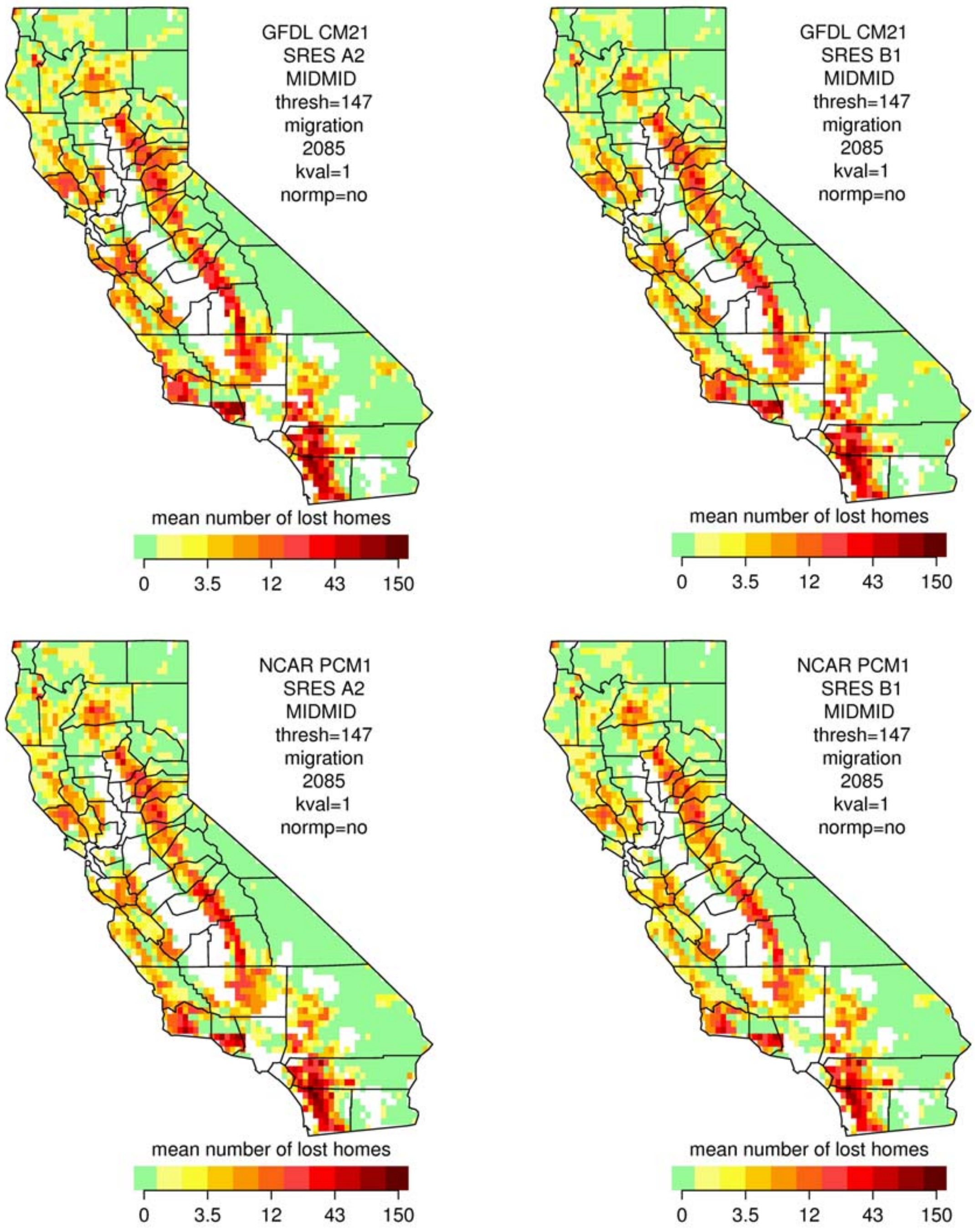

Figure 4. Annual Residential Wildfire Risk in 2085 for A2 and B1 expressed as the mean number of lost homes, for two different climate models.

3.3. Illustrative Monetary Impacts

Table 3 displays example monetary impacts derived using the methodology described in Section 2.4, using the base year 2000 value of $211,500. Each value in the table represents a plausible monetary impact (in billions of 2000 $US) due to lost home value in the center year of each period (i.e., 2020, 2050, and 2085). We emphasize that the particular values are highly speculative. Even though the ranges in any given year are already fairly wide, there are still many factors we do not consider that could strongly affect the results. These include deviation from the population trajectory that we utilize, as well as different housing value trajectories, the impact of local variation in housing prices, and the deployment of technologies for better protecting homes in the face of wildfire, and changes in fire severity. Nevertheless, we can see from this chart that *average* annual damages on the order of billions of dollars are quite plausible beginning mid-century. In general, the higher emissions A2 scenario seems to allow for potentially worse outcomes, though the difference is slight in any given time period. It should also be noted that the maximum values shown are associated with parameter combinations that were outside the year 2000 range, and would require a somewhat implausible worsening of effective fire protection techniques, though sprawling growth patterns and changing fire regimes could have this effect.

Table 3. Plausible estimates for aggregate average annual monetary damages summed across the State of California. The 'Min' and 'Max' columns represent the bounds of cases we explored. The 'Min' and 'Upper' columns represent the bounds from parameter combinations consistent with Year 2000 damage estimates.

Summary Statistics for Aggregate Example Damages

	2005-2035			2035-2065			2070-2100		
	Min	Upper	Max	Min	Upper	Max	Min	Upper	Max
SRES A2	0.050	0.48	2.4	0.20	2.3	13	0.68	14	80
SRES B1	0.047	0.45	2.6	0.21	2.5	13	0.53	11	62

Figures are in billions of undiscounted Year 2000 dollars and represent possible monetary impacts in a representative year during each period.

3.4. Discussion of Uncertainties and Sources of Error

Our model of fire risk is subject to a multitude of uncertainties. These include those uncertainties that affect the modeled wildfire burned areas used as inputs, and additional uncertainties about how households distributed on the landscape are interacted with wildfire burned area to generate a meaningful measure of risk. As can be seen by referring to Table 2, these uncertainties have the potential to impact the results by a significant factor, with relative risks spanning all the way from 1.6 to 8.15 for the period centered around 2085.

The primary uncertainties explicitly modeled on the exposure side and which contribute to the variance in our results include the form of the exposure scaling function, and the threshold household density for considering a pixel too urban to be subject to wildfire. In this modeling exercise, we do not perform a thorough sensitivity analysis to estimate marginal effects of changing these uncertain parameters. Rather, our focus is on ensuring we have captured a reasonably wide range of plausible conditions, and illustrated the impact they may have when propagated through to our outcome measure of interest. Further work to explore the effect of these uncertainties in more detail may be warranted if more reliance is to be placed on the precise numeric outcomes.

While we believe we have adequately addressed the explicitly modeled uncertainties with respect to the qualitative conclusions of this report, the results generated are also subject to potential sources of error not explicitly considered in the modeling. In particular, the model of risk may be insufficient to capture important interactions and hidden costs. For example, perhaps the decrease in exposure with increasing density comes at sizable increase in expenditures and risk to firefighters (Headwaters Economics 2008). In general, the magnitude of systematic errors is diminished by our relative risk measure, but this is not the case if the effects are significantly nonlinear, or if certain interaction effects qualitatively change over time (for example, through radically different fire management policies).

Another important source of uncertainty we do not consider is the technological and management responses to mitigate the damages. Primarily, these responses include the use of defensible space around homes, combined with home construction technology that is designed to withstand the presence of wildfire. Many new home construction techniques were introduced during the twentieth century, and we may assume further innovations throughout the twenty-first century, although the impact of fire-mitigating technological innovations will be reduced in proportion to their actual adoption, which may or may not be significant. Modeling the presence of these technologies in conceptually accurate detail is at present infeasible, though future study within our current framework could explore the potential impacts via changes to our exposure scaling function over time. Additionally, the ability of technology and forest management to mitigate exposed value may also vary geographically based on fire and vegetation type. While vegetation plays an explicit role in our fire model, its potential effect on fire severity and thus value lost is not incorporated into our estimates of exposed value. Both new technologies and the impact of these fire regime changes could be represented by reducing the area under the exposure scaling function in different time periods and regions.

4.0 Conclusions

Our modeling exercise demonstrated the following key results:

- Residential wildfire risk increases over time for all climate scenarios.
- The difference between an A2 climate scenario and a B1 climate scenario is minimal through mid-century, but some differences emerge in the period 2070–2100, with the A2 scenario leading to approximately 20–30 percent higher risk of property losses from fire.

In addition, our particular modeling approach and assumptions led to the following secondary findings, which should be interpreted with greater caution due to their greater sensitivity to the specifics of the modeling process:

- A tripling and even quadrupling of residential wildfire risk is quite plausible by mid-century, with even greater increases by the end of the century.
- The general spatial distribution of fire risk is mostly independent of climate scenarios, though most areas see higher risks under an A2 scenario. In addition, the very strong correlation between risk and population implies a large role for mitigation of risk through policies affecting ignitions of wildfires and the vulnerability of homes.
- The average annual cost associated with homes lost to wildfire could easily be in the billions of dollars by mid-century (in undiscounted year 2000 dollars), and under our assumptions, will almost always be at least in the tens of millions of dollars.

All of our findings, especially those dealing with absolute numeric estimates (rather than comparisons between scenarios), should be taken as illustrations of plausible futures under various sets of consistent assumptions. They are not predictions, and they are contingent on one particular growth scenario and assumptions of constant fire-protection technology. However, we did take many steps to account for some of the uncertainties involved, and these explorations demonstrated robustness in the key findings, which should provide some confidence that they accurately capture the nature of climate change's impact on the residential wildfire risk in California. Lastly, it should be remembered that residential wildfire impacts represent only a fraction of the impacts that climate-induced changes in wildfire patterns may have on California over the remainder of this century.

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Appendix

Specification of Uncertainties

Appendix: Specification of Uncertainties

Our model is subject to the uncertainties of both the fire probability model as well as the exposure estimation model. Some of these were described above, but we enumerate them completely here, with some additional discussion. Here we take the climate scenario itself (A2 or B1) as well as the spatially explicit growth scenario as given, and discuss uncertainties in form and parameter values contingent on the climate and growth scenario. Except where noted, every combination of these parameters was sampled (a full factorial design), leading to an initial sampling of 72 combinations for most periods, though we eventually ruled out some parameter combinations as entirely unrealistic.

Non-growth related uncertainties:

Climate-based vegetation migration: A binary variable indicating whether or not vegetation fractions are allowed to adapt over time to changing fire and climate conditions.

Climate model: Given emissions scenarios produce different changes in climate depending on the climate model that relates emissions to their climate impacts. This analysis uses the output of three different models: GFDL CM2.1, NCAR PCM3, and CNRM-CM3.

Uncertainties affecting both fire probabilities and exposure estimates:

Threshold urban density: What value of housing density, in units of household per square kilometer, is considered the threshold for a pixel being too dense to be subject to wildfires? In this analysis we use 147 and 1000, which are based on the upper and lower bounds for suburban density as defined in the ICLUS scenarios.

Growth-vegetation interaction: An ordered indicator for the method by which new residential growth affects vegetation fraction existing in a given gridcell. There are three options, which either minimize or maximize vegetation fraction remaining in a gridcell given new growth, and an option for allotting new growth proportionally to the area fraction already occupied by vegetation. Model results proved largely insensitive to this variable, so results presented here use only the proportional option.

All of the above are discussed in more detail in the companion Westerling et al. report (Westerling et al. 2009). Discussion of the climate and adaptation models can be found in text, while the threshold values and growth-vegetation interactions are thoroughly discussed in Appendix 1 of that report.

Uncertainties affecting exposure estimates only:

Concavity of exposure scaling function: The exposure scaling function scales the number of households in a pixel down to the number considered at risk for wildfire damages, as a function of density. This is described thoroughly in Section 2.2—we consider three parameter values (1/3, 1, and 3), each leading to different concavities in the exposure scaling function. As discussed in section 2.5, we find that the value of 3 is entirely unrealistic, so we do not consider that parameter combination in presenting our results.

Normalization of the exposure scaling function: The exposure scaling function can be interpreted as capturing two different effects: One is the simple effect that wildfire is not likely to spread beyond a certain "depth" into a group of houses (e.g., beyond 3 "rows")—due to a combination of suppression efforts and physical interactions between fire, structures and open space like roads—though inter-structure spread is a documented phenomenon (Institute for Business & Home Safety 2008). The scaling also captures the effect that the probability of a fire reaching a particular pixel is diminished in some proportion to the number of households in that pixel, via suppression efforts and pre-fire management efforts such as the creation of defensible space. However, this latter effect is also captured to some degree by inclusion of the population variable in the fire probability model. This means that if the relative magnitude of the first effect is small compared to the latter effect, the exposure scaling function will over-estimate the reduction in risk. If the second effect was perfectly accounted for in the fire probability model, it would be appropriate to additionally rescale the exposure function so that total probability was preserved. This is done by dividing by the area under the scaling curve (which will be less than one). It is unlikely that the true behavior is modeled at either extreme, so we consider both, and take rescaling as a binary uncertainty in the model. In reality, this does not need to be a binary variable, and future work should consider values between zero and one. Our calibration exercises also found that normalizing the scaling function led to unrealistically high values for the year 2000, so we did not utilize that parameter setting in futher analysis.

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